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Müller, Karsten

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German Forecasters' Narratives – How Informative are German Business Cycle Forecast Reports?

Karsten Müller*†

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Abstract

Based on German business cycle forecast reports covering 10 German institutions for the period 1993–2017, the paper analyses the information content of German forecasters' narratives for German business cycle forecasts. The paper applies textual analysis to convert qualitative text data into quantitative sentiment indices. First, a sentiment analysis utilizes dictionary methods and text regression methods, using recursive estimation. Next, the paper analyses the different characteristics of sentiments. In a third step, sentiment indices are used to test the efficiency of numerical forecasts. Using 12-month-ahead fixed horizon forecasts, fixed-effects panel regression results suggest some informational content of sentiment indices for growth and inflation forecasts. Finally, a forecasting exercise analyses the predictive power of sentiment indices for GDP growth and inflation. The results suggest weak evidence, at best, for in-sample and out-of-sample predictive power of the sentiment indices.

Keywords: Textual analysis, Sentiment, Macroeconomic forecasting, Forecast evaluation, Germany

JEL classification: C53, E32, E37, E66

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†University of Applied Sciences Merseburg, Eberhard-Leibnitz-Straße 2, D-06217 Merseburg / Germany, Mail: karsten.mueller@hs-merseburg.de.

1 Introduction

German business cycle forecast reports offer quantitative point forecasts and qualitative text data for growth and inflation, among other variables. The qualitative texts describe forecasters' views on the macroeconomic situation and development. And, the narratives also express the forecasters' expectations about the future development of the economy. Using the narratives, the forecasters' expectations can be objectified by applying textual analysis methods to generate sentiment indices. The key issue is to analyse whether the forecasters' narratives contain additional information beyond the quantified forecasts.

The evaluation of German and international business cycle forecasts has traditionally focused on the analysis of quantitative point and density forecasts. A large body of literature has addressed the accuracy and efficiency of German macroeconomic forecasts (see e.g. Heilemann and Stekler, 2013; Fritsche and Tarassow, 2017; Döpke et al., 2019, and the literature cited therein). To sum up the general results, three key insights can be concluded. First, macroeconomic forecasts for Germany are (mostly) unbiased, but inefficient (see e.g. Döpke et al. (2010) and Krüger and Hoss (2012)). Second, there is no obvious tendency of the forecast errors to increase or decrease (Heilemann and Stekler, 2013). Third, no forecaster's performance is uniformly superior (Döpke and Fritsche, 2006), and there are not significant institutional differences in accuracy across a long time horizon (Döhrn and Schmidt, 2011).

Recently, another forecast evaluation approach, which uses qualitative text as data, has become increasingly popular. In this context, textual analysis methods are applied to convert qualitative text data into quantitative scores. The generated indices are used for forecast evaluation tests with numerical forecasts and realized values. Two major strands of the literature can be identified.

One strand will be subsumed here under the term 'elicited forecasts', which was used by Jones, Sinclair, and Stekler (2020). This concept applies a manual scoring procedure to quantify qualitative assessments about the future stance of the economy. Goldfarb, Stekler, and David (2005) mapped newspaper articles published during the *Great Depression* into an index series using a scoring system to compare the quantified qualitative assessments with numerical forecasts and realized values. A series of forecast evaluation studies applied the developed scoring procedure of Goldfarb et al. (2005) in several contexts to generate *elicited forecasts* to evaluate them (see e.g. Lundquist and Stekler, 2012; Stekler and Symington, 2016; Mathy and Stekler, 2018). The recent analysis of Jones, Sinclair, and Stekler (2020) inves-

tigates the Bank of England's growth forecasts using *elicited forecasts* over the period 2005–2015. The more general research question as to whether the text contains additional information for the numerical forecasts is similar to this work. Jones et al. (2020) find that the economic development in the UK is accurately represented by the *elicited forecasts*. Moreover, regression results suggest informational content of the text index in the sense that they can improve the Bank of England's numerical growth nowcasts and one-quarter-ahead forecasts.

A second strand of the literature uses computational text analysis methods to generate text-based sentiment indices. Clements and Reade (2020) and Sharpe, Sinha, and Hollrah (2020) are two seminal related studies. The latter study applies textual analysis tools to measure the 'tonality' (the degree of optimism versus pessimism) of the Federal Reserve Board's Greenbooks and examines whether this measure has predictive power for the economic development over the period 1972–2009. The investigation shows some predictive power of the Greenbook tonality on Greenbook numerical GDP growth and unemployment forecasts, as well as on private GDP forecasts. The latter point implies that the sentiment index also covered policy-relevant information (Sharpe et al., 2020). Clements and Reade (2020) analyse whether the narratives in the Bank of England's Inflation Reports contain useful information about the future course of GDP growth and inflation between 1997 and 2018. Encompassing tests show some informational content for predicting GDP forecast errors for one and two quarters ahead, but no evidence that sentiment indices are useful to predict forecast revisions. Both studies use the dictionary-based approach to generate sentiment indices, and both studies show that 'an important element of economic forecasting is in the accompanying narrative' (Sharpe et al., 2020, p. 31).

Considering German forecasters' narratives, Fritsche and Puckelwald (2018) analyse the topics of German business cycle forecast reports using generative models. The authors find that textual expressions vary with the business cycle, which is in line with the hypothesis of adaptive expectations. In contrast to previously mentioned studies, the authors do not apply a sentiment analysis to generate and test indices.

There is a broader and growing literature in (computational) textual analysis in economics, finance, and accounting (see e.g. Loughran and McDonald, 2016; Gentzkow et al., 2019, and the literature cited therein). The following examples give a selective overview of literature that is related to this paper. One strand of the literature concerns the predictability of stock market activity. Tetlock (2007); Tetlock et al. (2008); Garcia (2013) use a dictionary-based approach to generate sentiment indices via news coverage. Loughran and McDonald (2011, 2016) developed a finance-specific dictionary to im-

prove the forecasting performance relative to existing linguistic dictionaries. Jegadeesh and Wu (2013); Manela and Moreira (2017) apply text regression methods to predict stock market outcomes, while Jegadeesh and Wu (2013) show that text regression-based sentiment indices are superior to sentiment indices based on Loughran and McDonald (2011) dictionary in an out-of-sample forecast environment. The analysis of central bank communication is another topic in text mining. Jegadeesh and Wu (2017) find incremental information value in the Federal Open Market Committee meeting minutes. The authors use a generative model to quantify the tone and the topics of texts. Tillmann and Walter (2018) apply dictionary-based sentiment indices to analyse the tone of Bundesbank and ECB speeches. They find significant divergences between the tone of the two institutions. An additional topic is about measuring policy uncertainty. Baker et al. (2016) developed the prominent economic policy uncertainty index (EPU) by analysing news coverage with a dictionary method. Using a (nonlinear) text regression method to construct an EPU for Belgium, Tobback et al. (2018) show that they have improved the predictive power of the EPU.

This paper makes several contributions to the literature on forecast evaluation and textual analysis. First, German forecasters' narratives were converted into quantitative sentiment indices using dictionary methods and text regression methods. Second, to the best of the author's knowledge, this paper is the first in forecast evaluation to apply (linear) text regression approaches, and additionally, it uses a recursive estimation technique.

The purpose of the paper is to analyse German forecasters' narratives and the question as to whether the forecasters' stories and expectations contain additional information relative to numerical forecasts. Based on 534 business cycle forecast reports covering 10 German institutions from 1993 to 2017, the paper creates sentiment indices using text mining techniques. Regression results suggest that some sentiment indices can reduce the absolute magnitude of the quantitative forecast errors for GDP growth and inflation forecasts. German forecasters' narratives are informative for the accuracy of German business cycle forecasts. One explanation might be that forecasters' narratives contain useful information about the future stance of the German economy. An in-sample and out-of-sample forecasting exercise tests whether the sentiment indices can predict the evolution of German economic activity. Forecasting results indicate weak in-sample predictive power and modest out-of-sample predictive power of the sentiment indices.

The following section explains the methodology used to convert qualitative text data into quantitative sentiment scores. Section 3 describes the employed text corpus and numerical data. Section 4 analyses the empirical results, and Section 5 concludes and discusses these results.

2 Methodology - Sentiment Analysis

There are various computational analysis methods to connect word counts to attributes to generate sentiment indices, e.g. dictionary-based methods, text regression methods, generative models, and word embeddings (Gentzkow et al., 2019). This paper uses dictionary-based methods and text regression methods to convert qualitative text data into quantitative indices.

Furthermore, qualitative measures can only be directly related to macro-variables, provided that they are appropriately scaled (Clements and Reade, 2020, p. 1491). Hence, all weighted sentiment indices are standardized to have a mean equal to zero and a standard deviation equals to one. In order to avoid bias in the measure, all weighted sentiments are normalized by the total number of words per report to account for varying text lengths and numbers of documents per year (Fritsche and Puckelwald, 2018).

2.1 Dictionary-based method

Following Clements and Reade (2020) and Sharpe et al. (2020), the dictionary-based method is applied to develop sentiment indices. In fact, three well-established linguistic dictionaries are used to generate five different indices.

- First, the word list is prepared by Bannier et al. (2018). This is the German equivalent of the English original dictionary provided by Loughran and McDonald (2016). The last-mentioned word list is well established for textual analysis in finance- and accounting-specific contexts. The word list prepared by Bannier et al. (2018) includes over 2,200 positive and 10,000 negative word forms. The dictionary is binary coded for polarity in positive and negative terms.

- Second, there is a forecast-specific German dictionary based on Sharpe et al. (2020). According to Di Fatta et al. (2015), words have different connotations and meanings in different contexts, and sentiment indices have to be adapted to the content to which they have been applied. To this end, Sharpe et al. (2020) developed a forecast-specific word list which excludes words that have special meanings in an economic forecasting context. The word list contains 205 positive and 103 negative words (see Tables A2 and A3) and is binary coded like the previous one.

- Finally, there is the SentimentWortschatz (SentiWS) dictionary (Remus et al., 2010). The SentiWS dictionary contains a German-specific

word list for sentiment analysis. The current version (v2.0) contains about 16,000 positive and 18,000 negative word forms, and unlike the other two dictionaries, it includes weights for polarity within the interval of $[-1; 1]$.

Two different score systems will be applied for the two binary dictionary-based sentiments (hereinafter called 'Bannier' and 'Sharpe'). Sentiment score number one consists of the difference between positive word count, P, and negative word count, N, normalized by the total number of words, T, per report:

$$Sentimentscore_1 = (P - N)/T \tag{1}$$

The second sentiment score (polarity score) is defined as the quotient of the difference between positive and negative word counts and the sum of positive and negative words:

$$Sentimentscore_2 = (P - N)/(P + N) \tag{2}$$

In contrast, the SentiWS index is a continuous score. The score of each word sums up over all words and is normalized by the total number of words per report.

2.2 Automatic variable selection approach

The automatic variable selection approach, a promising text regression method (e.g., Pröllochs et al., 2018), is used to generate regression-based sentiment indices. In contrast to the dictionary-based method, here the required dictionary is not given and will be recursively estimated. In fact, the estimated parameters will be updated by expanding the estimation windows by one observation in chronological order (see 2.3). Generally, text regression methods introduce a regularization penalty that reduces the complexity, number, and size of the predictors included in the model. Penalized linear models use each word in the text corpus as explanatory variables, shrink non-informative noise variables to zero, and select decisive variables (Pröllochs et al., 2015).

As a result, regularization methods avoid multicollinearity problems of a large number of highly correlated regressors and find a trade-off between accuracy (bias) and uncertainty (variance). Regularization methods can serve as mathematical mechanisms to extract important terms, which is why it is a common tool for variable selection in data science (Pröllochs et al., 2018; Varian, 2014). Given a standard multivariate regression with y_i (dependent

variable) as a linear function of β_0 (constant) and x_j (explanatory variable), the penalty term of the form:

$$\lambda \sum_{j=1}^{P} \left[(1-\alpha)|\beta_j| + \alpha|\beta_j^2| \right] \tag{3}$$

can be added (Varian, 2014). Setting $\alpha = 0$, the term 3 reduces to the linear l_1-norm penalty $\lambda \sum_{j=1}^{P} |\beta_j|$, which represents the *least absolute shrinkage and selection operator* (LASSO) introduced by Tibshirani (1996). Formally, the LASSO estimator is given by (Pröllochs et al., 2015):

$$\hat{\beta}_{LASSO} = \arg\min_{\beta} \sum_{i=1}^{N} \left[y_i - \beta_0 + \sum_{j=1}^{P} \beta_j x_{ij} \right]^2 + \lambda \sum_{j=1}^{P} |\beta_j| \tag{4}$$

where x_{ij} are the document terms (words), and y_i represents the 12-month-ahead fixed horizon growth and inflation forecasts as response variables. If $\lambda = 0$, the penalty reaches zero, and we get the classical OLS estimator by simply minimizing the residual sum of squares. The higher λ, the larger the penalty shrinkage gets, with the result that more coefficients end up being zero. The optimal λ^* is estimated by minimizing the mean squared error (MSE) (Dimpfl and Kleiman, 2019):

$$MSE_{CV}(\lambda) = \frac{1}{K} \sum_{i=1}^{K} \frac{1}{n_i} ||y_i - X_i \hat{\beta}_{LASSO}^{-i}||_2^2 \tag{5}$$

using an established 10-fold cross-validation, where n_i is the size of ith subsample. Therefore, the data are split into K subsets, one part i is removed, the coefficients $\hat{\beta}_{LASSO}^{-i}$ are estimated, and the cross-validated $MSE_{CV}(\lambda)$ is calculated for any given value of λ.

In contrast, setting $\alpha = 1$ shortens the term 3 to the quadratic l_2-norm penalty $\lambda \sum_{j=1}^{P} \beta_j^2$, and the ridge estimator is implemented (Pröllochs et al., 2015):

$$\hat{\beta}_{Ridge} = \arg\min_{\beta} \sum_{i=1}^{N} \left[y_i - \beta_0 + \sum_{j=1}^{P} \beta_j x_{ij} \right]^2 + \lambda \sum_{j=1}^{P} \beta_j^2 \tag{6}$$

Again, the tuning parameter λ is the regularization penalty. The quadratic penalty l_2-norm follows similar characteristics to the LASSO penalty: if λ reaches zero, we get OLS coefficients; if λ moves towards infinity, the coefficients come down to zero. However, in contrast to the LASSO regularization, the ridge estimator does not set explicitly some coefficients equal to zero

(Pröllochs et al., 2015).[1] Again, the optimal λ^* is estimated by minimizing the MSE using 10-fold cross-validation.

Equations 4 and 6 are used to estimate the LASSO and ridge regression coefficients $\hat{\beta}_{LASSO}$ and $\hat{\beta}_{Ridge}$. The magnitude of $\hat{\beta}_{LASSO}$ and $\hat{\beta}_{Ridge}$ serve as the weight and a measure of variable importance, specifying which variables (words) are included in the final dictionary (Pröllochs et al., 2015). A linear rule is then applied to calculate document ith sentiment score. Again, the document's score is defined as the continuous score normalized by the total number of words.

2.3 Recursive estimation

In order to guarantee that no information is produced and used for tests for forecast efficiency and predictive power that are (hypothetically) not known for forecaster in time t, a recursive estimation technique will be applied for sentiment indices based on the automated variable selection approach. First, a sufficiently large text corpus is generated as a basis (pre-estimation corpus) using business cycle forecast reports from the period 1993–1998, including 74 observations. Second, based on the pre-estimation corpus, a recursive estimation approach is applied, expanding the estimation windows by one observation per estimation in chronological order. In fact, the following procedure is executed in each recursive estimation step: First, the extended text corpus is established and weighted; second, the optimal λ^* is estimated by minimizing the MSE using 10-fold cross-validation; third, LASSO and ridge estimator (Equations 4 and 6) are used to estimate the respective dictionaries and weights ($\hat{\beta}_{LASSO}$ and $\hat{\beta}_{Ridge}$); finally, the respective sentiment (document) score is calculated and stored in a common series.

3 Corpus and Data

3.1 Textual analysis - the corpus

The plain corpus includes business cycle forecast reports for Germany issued by 10 institutions with different institutional backgrounds. First, the corpus covers the six largest economic research institutes in Germany that are formally politically and economically independent. These comprise the

[1] Ridge regularization is introduced as an opposite of LASSO because the ridge estimator cannot benefit from a parsimonious model (Pröllochs et al., 2018). Therefore, the elastic net, a mixture of both regularization methods, is not absolutely necessary for this investigation.

five publicly founded institutes, the Ifo Institute Munich (Ifo), the Berlin Institute (DIW), the Essen Institute (RWI), the Halle Institute (IWH), the Kiel Institute (IfW), and the privately funded Hamburg Institute (HWWI).[2] Second, the corpus contains institutes that are funded by interest groups: the employer's institute of the German economy located in Cologne (IW Köln), and the trade union's macroeconomic policy institute (IMK). Third, the corpus includes the 'joint diagnosis' (GD), the economic projection of the leading research institutes as an institution within the process of economic policy advice. Fourth, the corpus covers a financial institution, the Bundesbank. The German central bank is another formally politically and economically independent public institution.

The entire corpus contains 534 documents.[3] There is a wider range of potential business cycle forecast reports for Germany than the selected institutes that did not meet the defined criteria. For the selection, a range of criteria was checked:

- Business cycle forecast (sub-)section: Business cycle forecast reports are heterogeneous in size and content. Some reports are structured into different subsections like recent national or international economic development, business cycle forecasts, economic policy advices, or methodological explanations. Other reports are miscellaneous texts of various themes and cannot be split in a meaningful way. Therefore, business cycle reports should contain a clearly defined forecast (sub-)section.

- Time range: The corpus covers business cycle forecast reports for Germany from 1993 to 2017 to circumvent the German reunification and possible misspecification for East and West Germany.

- Forecasters' experiences: Continuity and regularity of publication within the examined period ensure forecasters' experiences in the field of economic forecasting, ensuring a sufficient level of homogeneity in language across institutes.

- Language homogeneity: The (relatively short) period of 25 years as well as forecasters' experiences assures a sufficient degree of homogeneity in language over time.

[2]Until 2005, the HWWI was known as HWWA and mainly funded by public money. It became a privately funded institute in 2006.

[3]See Table A1 for an overview.

- Quantitative forecast availability: To use a comparative sample for growth and inflation forecast analysis, only business cycle forecast reports with a calculable fixed horizon forecast for growth and inflation will be used. The availability of numerical point forecasts of growth and inflation for the current and next year restricts the number of incorporated forecast reports (see 3.2).

- Forecasting date: The forecasting date is distributed over the whole year, depending on respective institutional practice and the frequency of publication. In most cases, the frequency of publication is bi-annual or higher (see appendix 5).

- Text availability: Another criterion was the public availability of business cycle forecast reports, which is why private institutes like banks are not included.

Finally, 534 business cycle forecast reports for Germany issued by 10 institutions are used for the creation of the corpus. In the first step of textual analysis, data cleaning and linguistic pre-processing are applied to all texts. In fact, line breaks, numbers and words with fewer than four characters are eliminated, lower cases were introduced, stopwords (e.g. from German linguistic stopword lists or names) and sparse terms where a word that occurs in less than 10% of documents are removed. With reference to Zipf's law (Zipf, 1949), the texts are weighted with their term frequency—inverse document frequency (tf-idf).[4] Zipf's law for empirical language implies that a word's frequency is inversely proportional to its rank. Consequently, the corpus is adjusted for that symptom. Figure 1 shows the wordcloud of the weighted corpus. The wordcloud sort terms frequency in descending order. The larger the word, the more often the term occurs. The wordcloud shows that the weighted corpus includes a lot of important forecast-specific vocabulary, for example 'Anstieg' (growth), 'Prognose' (forecast), and 'Exporte' (exports).[5]

Figure 2 illustrates a frequency analysis of German boom and recession synonyms, aggregates over years and across institutes. Again, we consider a relative measure to account for varying text lengths and numbers of documents per year. We see some frequency patterns of economic key terms

[4]The principle behind the tf-idf weighting scheme is that the more often a word appears in a document, the more important it is (term frequency). But, the more the word appears in all documents, the less important it is (inverse document frequency). The tf-idf weighting scheme is a commonly used metric in text analysis literature (see e.g. Loughran and McDonald, 2011; Sharpe et al., 2020).

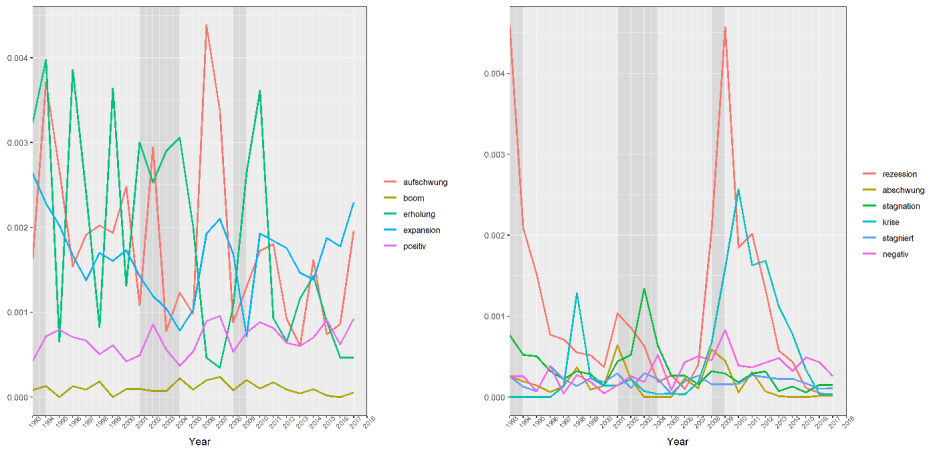
[5]Nevertheless, the pre-processed corpus contains some meaningless terms as 'gegenüber' (in relation to) or 'deutlich' (obvious). To avoid a selection bias, the linguistic stopword lists were not manually expanded.

Figure 1: Wordcloud of German business cycle forecast reports

Notes: Own illustration.

Figure 2: Relative frequency of terms

(a) Economic boom synonyms (b) Economic recession synonyms



Notes: Authors' own illustration. Relative measure: absolute count of the respective word aggregate per year in relation to the number of words per year. Shaded area: recession phases according to the 'business cycle peak and trough dates' from Economic Cycle Research Institute (2020).

that are directly related to the business cycle development. For example, the term 'Rezession' (recession) rises strongly during the reunification crisis, in the early 1990s, as well as during the dotcom crisis in the early 2000s, reaching a global peak during the financial crisis of 2008–09. The results are similar to the outcome obtained by Fritsche and Puckelwald (2018).

Finally, Porter's stemming algorithm (Porter et al., 1980) is used to truncate the different word forms to its base forms. [6]

3.2 The sample

The incorporated business cycle forecast reports for Germany typically contain numerical fixed event forecasts of growth and inflation for the current and next year. Depending on the forecast date, the forecast horizon of fixed event forecasts varies from one up to 11 months. Heilemann and Müller (2018) show in a forecast evaluation study for Germany that forecast accuracy decreases with increasing forecast horizon, and that differences in forecast accuracy are mainly determined by the different timings of the production of the forecasts.[7]

Furthermore, uncertainty and cross-sectional dispersion of fixed event forecasts show a pronounced seasonal pattern (Dovern et al., 2012). Consequently, fixed-horizon forecasts are used to reduce different forecast horizons within one quarter. Moreover, forecast narratives cannot distinguish between different forecast horizons within a quantitative textual analysis. The fixed horizon forecasts allow us to synchronize qualitative and quantitative forecast horizons more efficiently.[8]

The method of Dovern and Fritsche (2008); Heppke-Falk and Hüfner (2004); Smant (2002)

$$\hat{y}_{i,t}^{12} = \frac{4-q+1}{4}\tilde{y}_{i,t}^{0} + \frac{q-1}{4}\tilde{y}_{i,t}^{1} \tag{7}$$

[6] German is a morphologically rich language and the text corpora is a specific economic text corpora, and therefore, the meaning of a word is crucial. Stemming reduces different word forms to its base forms and to retain the meaning and semantic interpretation of the word (Jivani, 2011). Porter's stemming algorithm is one of the best stemming algorithms; it has a lower error rate and it is a light stemmer (Jivani, 2011). Thus, the stemming procedure reduces complexity without losing the meaning of the word form. In contrast, lemmatization reduces the word forms to its root forms and the semantic interpretation can be lost (Jivani, 2011).

[7] An analysis of forecast revision patterns shows an inverse L-curve relationship between accuracy and shortening forecast horizon (Heilemann and Müller, 2018).

[8] As a result, the assumption that the narratives only describe the next 12 months is introduced. This assumption should be less critical if we consider that we only cut a few months, at worst, in the most uncertain forecast horizon at the end.

is applied to construct 12-month-ahead fixed-horizon forecasts for growth and inflation. Given current ($\tilde{y}^0_{i,t}$) and next ($\tilde{y}^1_{i,t}$) year fixed event forecast, the 12-month-ahead fixed-horizon forecast is approximated as a quarterly weighted average of their share in both years. Besides, seasonally adjusted and finally revised real GDP is used for realized GDP growth (quarterly data, source Federal Statistical Office (2019b)). Finally, the revised consumer price index is used for actual inflation outcome (monthly data, source Federal Statistical Office (2019a)).[9]

The forecast error is defined as $e_t = A_t - P_t$—the realized value in period t minus the forecast made in period $t - j$. Hence, a positive forecast error represents an underestimation of the growth (inflation) rate, and vice versa, whereas a negative forecast error corresponds to an overestimation.

Table 1: Descriptive statistics on forecast accuracy in Germany, 1993–2017

	Growth forecasts:	Inflation forecasts:
Number of observations	534	534
Mean Error	-0.051	-0.135
Mean Absolute Error	1.715	0.685
Root Mean Squared Error	2.578	0.862
Theil's Inequality Coefficient	1.000	0.546
Number of Overestimations	274	292
Number of Underestimations	260	242

Notes: Source: Authors' own calculations. The Mean Error: ME $= \frac{1}{T}\sum_{t=1}^{T} e_t$, where e_t is the forecast error in each period, defined as actual A_t (in t) minus predicted P_t (in $t-1$ for period t). $t = 1, ..., T$ is the time index. The Mean Absolute Error: MAE $= \frac{1}{T}\sum_{t=1}^{T} |e_t|$. The Root Mean Squared Error: RMSE $= \sqrt{\frac{1}{T}\sum_{t=1}^{T} e_t^2}$. The Theil's Inequality Coefficient: Theil U $= \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}|e_t^2|}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}|A_t^2|}}$

Table 1 provides an overview of some standard measures of forecast evaluation (see for example Fildes and Stekler, 2002) for the pooled data of the introduced sample. On the whole, the error measures correspond to previous forecast evaluation studies for Germany (Heilemann and Stekler, 2013; Döpke et al., 2019). The ME is nearly zero, indicating unbiased forecasts. Growth forecasts MAE and RMSE are on average large compared to Heilemann and Stekler (2013); Döpke et al. (2019) due to the forecasting error in the *Great Recession* 2008/2009.[10]

[9] In forecast evaluation contexts, it is appropriate to use first published (real-time) data or the last available revised data (Döpke et al., 2019). Here, the revised data are used because of data availability.

[10] Calculations without the period of the *Great Recession* in 2008/2009 results in similar

4 Empirical Results

4.1 Sentiments' Characteristics

Table 2 gives an overview of sentiment characteristics.

Table 2: Overview dictionaries metrics[a)]

Feature/dictionary	Bannier (1,2)	Sharpe (1,2)	SentiWS	LASSO (GDP)	LASSO (inflation)	Ridge (GDP)	Ridge (inflation)
Dictionary type	Binary	Binary	Weighted	Weighted	Weighted	Weighted	Weighted
Total entries	7619	292	22972	71	69	2359	2359
Positive entries	1363	196	10863	42	38	1257	1161
in %	17.9	67.1	47.3	59.2	55.1	53.3	49.2
Negative entries	6256	96	12109	29	31	1102	1198
in %	82.1	32.9	52.7	40.8	44.9	46.7	50.8
Average score	-	-	-0.0515	-0.0032	0.0002	0.0000	0.0000
Standard deviation	-	-	0.2153	0.0302	0.0159	0.0021	0.0017

Notes: Own representation. [a)]: Full sample example.

Considering dictionary metrics as positive and negative entries and standard statistical measures, Table 2 shows how different the individual sentiment approaches work. The ridge estimation results show that the ridge estimator does not explicitly set some coefficients equal to zero. In contrast to the LASSO estimator, the ridge approach selects much more words as its LASSO counterpart.

Tables A4–A7 list in a full sample example the (stemmed) dictionaries and weights generated by the automated variable selection approach. Table A4 shows the estimated 71 words and their coefficients according to LASSO regression with real GDP growth forecasts as the response variable (hereinafter 'LASSO_GDP_P'). The term with the most positive weight is 'upswing' ('Aufschwung'), which in German is also a synonym for 'boom' or 'recovery', whereas 'drastic' ('drastisch') is the word with the most negative coefficient. The list of plausible words and weight with respect to GDP development is long, i.e. 'export dynamic' ('Exportdynamik'), 'continuation' ('Fortsetzung'), 'lively' ('schwungvoll') with positive coefficients, or 'deep' ('tief'), 'layoffs' ('Entlassungen'), and 'shrink' ('schrumpfen') with negative coefficients. Nevertheless, the list contains few outliers whose economic sense is not immediately clear, e.g. 'a third' ('drittel'), or where the words have a non-intuitive weight, such as 'recover' ('erholen').[11]

error measures.

[11] An extended pursuit of stopwords could reduce some 'outliers' to a minimum. But first, the objective of this paper is not to find the best stopword list, and, second, the few outliers should not matter from a purely statistical point of view.

Similar patterns can be observed in other text regression-based dictionaries. Table A5 lists the estimated 69 words and weights according to LASSO regressions, with inflation forecasts as the response variable (hereinafter 'LASSO_INF_P'). Tables A6–A7 list ridge regression results for real GDP growth forecasts (hereinafter 'Ridge_GDP_P') and inflation forecasts (hereinafter 'Ridge_INF_P'). Both tables list the top 30 estimated words with the largest positive and negative coefficients.

Figures 3 and 4 give a visual impression of the generated sentiment indices. The figures illustrate the sentiment values per business cycle forecast report aggregated over years and across institutes, in combination with the realized real GDP growth, or inflation rate, respectively. Panels (a) to (i) present for each sentiment specification the aggregate sentiment value per year on the left axis (solid line), and the realized value of GDP growth, respective inflation, on the right axis (dashed line).

Considering each of the panels from (a) to (i) separately, we can conclude that each sentiment specification varies in its pattern. Concerning, for instance, the *Great Recession* in 2008–09, it can be seen that some sentiment indices are closer to the real development, i.e. LASSO GDP forecast in Figure 3, whereas some sentiment indices have a longer time lag, i.e. Sharpe 1 in Figure 3. Other sentiment indices are even ahead of the real development, i.e. Sharpe 2 in Figure 4. Another picture illustrates a (partly) countercyclical behaviour. For example, Bannier1 and Bannier2 in Figure 4 show this countercyclical behaviour, which could be explained by a huge time lag or an opposite polarity of terms.

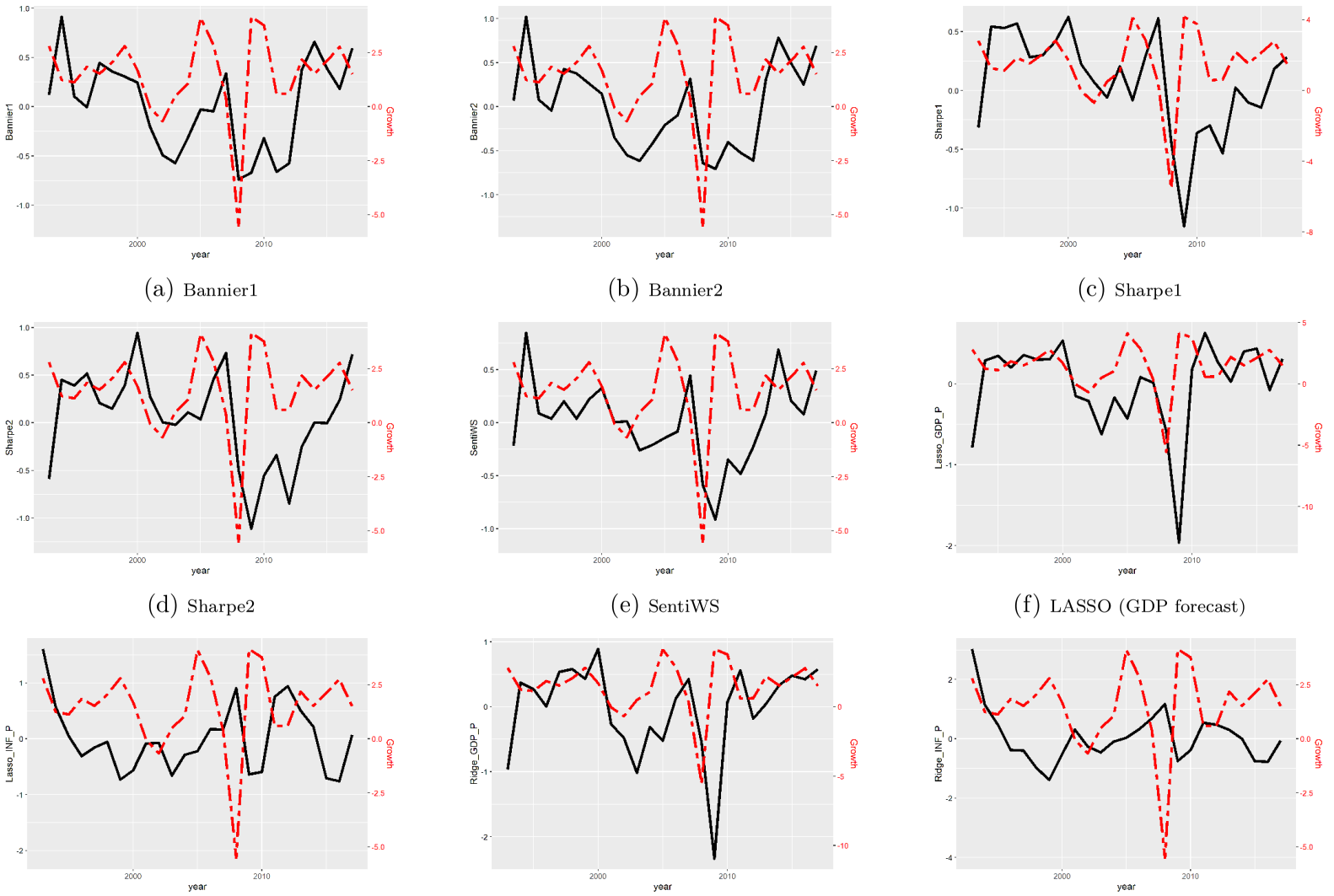
In summary, the generated sentiment indices differ across patterns and in amplitude, as well as in terms of time lag and lead.

4.2 Forecast efficiency

Forecast efficiency analysis is used to test whether the narratives of German business cycle reports contain useful information for the numerical forecasts of German forecasters. More precisely, we test whether the sentiment indices can be used to improve the accuracy of the quantitative point forecasts. In particular, we test for weak and strong efficiency of forecasts by using the specification of Holden and Peel (1990):

$$e_{i,t} = \beta_{0,i} + \beta_1 e_{i,t-1} + \beta_2 Sentiment_{i,t-1} + u_{i,t}, \tag{8}$$

Figure 3: Sentiment indices and realized growth, aggregate over years and institutes



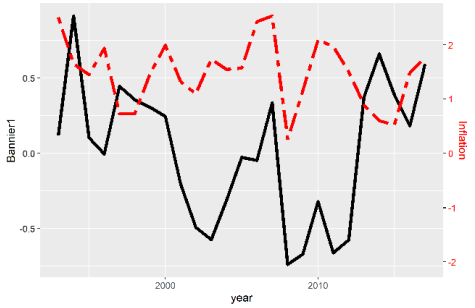
(a) Bannier1 (b) Bannier2 (c) Sharpe1

(d) Sharpe2 (e) SentiWS (f) LASSO (GDP forecast)

(g) LASSO (inflation forecast) (h) Ridge (GDP forecast) (i) Ridge (inflation forecast)

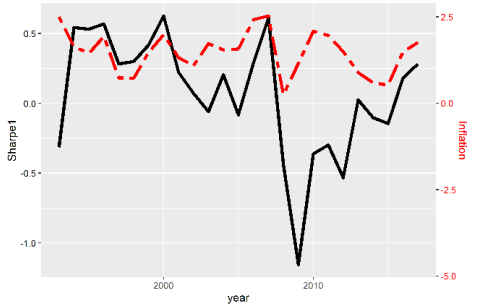
Note: Own calculations. Sentiment (solid line, left axis) and realized GDP growth (dashed line, right axis).

Figure 4: Sentiment indices and realized inflation, aggregate over years and institutes



(a) Bannier1

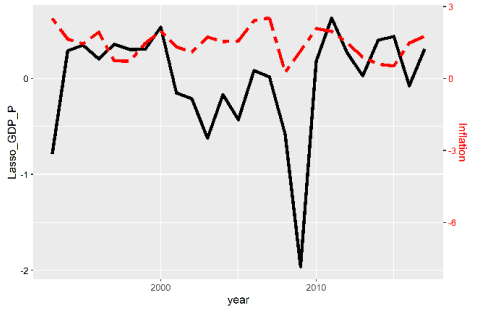
(b) Bannier2



(c) Sharpe1

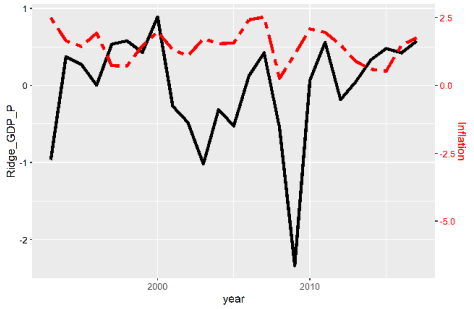
(d) Sharpe2

(e) SentiWS



(f) LASSO (GDP forecast)

(g) LASSO (inflation forecast)



(h) Ridge (GDP forecast)

(i) Ridge (inflation forecast)

Note: Own calculations. Sentiment (solid line, left axis) and realized inflation (dashed line, right axis).

and test the joint null hypothesis

$$H_0 = \begin{cases} \beta_{0,i} = 0 \\ \beta_1 = 0 \\ \beta_2 = 0. \end{cases} \tag{9}$$

In Equation 8, $e_{i,t}$ is the forecast error of forecaster i in time t, $\beta_{0,i}$ is institution's i individual effect, $e_{i,t-1}$ is the institution's forecast error made in $t-1$, $Sentiment_{i,t-1}$ is the forecaster's sentiment index at time $t-1$, and $u_{i,t}$ is the error term. Forecasts are weakly efficient if the forecast errors are not autocorrelated, and forecasts are strongly efficient if there is no variable that helps to predict the forecast errors, including the lagged forecast error. Optimal forecasts should consider all available information at the date of the forecast. A fixed effects estimation approach is used to account for individual institutional effects, such as different forecast horizons. Estimates are corrected for serial and cross-sectional correlation. According to Gaibulloev et al. (2014), panel-corrected standard errors (PCSE) suggested by Beck and Katz (1995) are reliable for panel type T>N to deal with unit heterogeneity and panel heteroscedasticity, and the Nickell bias (Nickell, 1981) is negligible.[12] Comparable forecast evaluation studies have used this kind of robust standard errors (see, among others, Keane and Runkle, 1990; Kauder et al., 2017; Döpke et al., 2019).

Table 3 presents the estimated parameters and the standard errors (in parentheses) of the individual coefficients and the p-value [in brackets] for the joint efficiency test. In almost all cases, the weak efficiency condition of no serial correlation of the forecast errors has to be rejected for GDP growth forecasts. Moreover, test results with sentiment indices indicate several significant influences of forecasters' narratives for forecast accuracy. For both Sharpe sentiment indices, as well as for all text regression-based sentiment indices, the null of no correlation has to be rejected at a conventional significance level. The negative coefficients indicate that a higher sentiment value correlates with a higher GDP prediction in that smaller (or negative) forecast errors imply higher forecast values. In addition, all specifications reject the joint test on efficiency. But it is not clear whether the autocorrelated forecast error or the sentiment indices are the reason for the rejection of the joint tests.

Considering inflation forecasts, again, the lagged forecast error has generally a significant influence on the forecast error of the following period, at

[12]Therefore, it is not necessary to employ the dynamic panel estimator proposed by Arellano and Bond (1991)

a conventional significance level. Moreover, we find some hints for explanatory power of the narratives on the numerical point forecast errors. Sharpe2 and the LASSO, as well as the ridge sentiment with inflation forecast as response variable, are significantly correlated with the forecast error. Both text regression-based sentiment indices are the only two out of nine specifications that also reject the joint efficiency hypothesis without having autocorrelated errors. The varying signs of sentiment indices' coefficients indicate sentiment indices with different polarity. Thus, rising inflation, e.g. the word 'inflation', could have both positive and negative weights, depending on the given dictionary (dictionary-based methods) and the used response variable (text regression methods).

The efficiency test results suggest that forecasters' narratives have informational power for the forecast errors at the time when the forecasts were made, implying that the numerical forecasts do not make efficient use of all available information. Previous studies (e.g., Döpke et al., 2010, 2019) confirm that forecasts for Germany are not strongly (in part weakly) efficient by not incorporating all available information. But they never test the narratives of the forecaster itself. Sentiment indices, based on business cycle forecast reports, seem informative for the accuracy of German business cycle forecasts.[13] Thus, forecasters' narratives contain information which is not exhausted by numerical forecasts. One explanation might be that the forecasters' narratives contain useful information about the future stance of the German economy.

4.3 Predictive power

To test whether the narratives of German business cycle forecast reports contain useful information for the future stance of the German economy, the paper applies an in-sample and an out-of-sample forecast exercise.

4.3.1 In-sample forecasting regressions

Following Estrella and Hardouvelis (1991); Stock and Watson (2003); Ferreira (2018), single forecasting equations are used to predict actual GDP growth and the inflation rate of changes. The in-sample and (pseudo) out-of-sample forecasting exercise tests whether text-based sentiment indices have predictive power for actual GDP growth and inflation. Similar methods were used to find predictors of economic activity (Estrella and Hardouvelis, 1991) or predictors of business cycle fluctuations (Ferreira, 2018). In order to do that,

[13] Robustness checks with the last known forecast error instead of the lagged forecast error support this finding. The results are available on request.

Table 3: Tests for efficiency of forecasts — 1999-2017.

	Dependent Variable: Growth Forecast Error[a)]									
Constant	-[b)]	0.079	0.078	0.052	0.052	0.077	0.086	0.056	0.083	−0.057
	-	0.132	0.132	0.131	0.130	0.132	0.128	0.127	0.125	0.124
lGDP_FE	−0.203***	−0.212***	−0.206***	−0.182***	−0.167***	−0.196***	−0.099*	−0.221***	0.002	−0.188***
	(0.057)	(0.058)	(0.058)	(0.057)	(0.057)	(0.057)	(0.057)	(0.054)	(0.058)	(0.052)
Bannier1		0.118								
		(0.135)								
Bannier2			0.032							
			(0.126)							
Sharpe1				−0.324**						
				(0.151)						
Sharpe2					−0.402***					
					(0.136)					
SentiWS						−0.152				
						(0.155)				
Lasso_GDP_P							−0.736***			
							(0.145)			
Lasso_INF_P								−0.761***		
								(0.124)		
Ridge_GDP_P									−1.093***	
									(0.166)	
Ridge_INF_P										−1.341***
										(0.159)
Observations	387	387	387	387	387	387	387	387	387	387
R^2	0.043	0.045	0.043	0.057	0.063	0.045	0.097	0.122	0.142	0.198
Efficiency test [p-value]	[<0.001]	[0.001]	[0.002]	[<0.001]	[<0.001]	[0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]
	Dependent Variable: Inflation Forecast Error[a)]									
Constant	-[b)]	−0.062	−0.062	−0.058	−0.058	−0.063	−0.063	−0.067	−0.065	−0.106
	-	0.042	0.042	0.042	0.041	0.042	0.042	0.039	0.042	0.037
lINF_FE	−0.109**	−0.108**	−0.108**	−0.121**	−0.132***	−0.109**	−0.109**	−0.045	−0.128**	0.067
	(0.050)	(0.050)	(0.050)	(0.050)	(0.051)	(0.050)	(0.052)	(0.047)	(0.054)	(0.047)
Bannier1		0.023								
		(0.045)								
Bannier2			0.019							
			(0.040)							
Sharpe1				0.073						
				(0.049)						
Sharpe2					0.113***					
					(0.043)					
SentiWS						−0.011				
						(0.047)				
Lasso_GDP_P							−0.0005			
							(0.049)			
Lasso_INF_P								−0.323***		
								(0.043)		
Ridge_GDP_P									0.046	
									(0.049)	
Ridge_INF_P										−0.568***
										(0.054)
Observations	387	387	387	387	387	387	387	387	387	387
R^2	0.013	0.013	0.013	0.020	0.030	0.013	0.013	0.157	0.015	0.269
Efficiency test [p-value]	[0.028]	[0.085]	[0.085]	[0.033]	[0.004]	[0.088]	[0.091]	[<0.001]	[0.062]	[<0.001]

Notes: Standard errors are in parentheses; p-values are in brackets. [a)]: Cross-section SUR (PCSE) standard errors and covariances (d.f. corrected) following the method of Beck and Katz (1995). [b)]: The function in R does not work with one-dimensional objects, it requires at least two explanatory variables. ***, **, and * denote rejection of the null hypothesis at the 1, 5, and 10 % significance level, respectively.

the sentiment indices are transformed by averaging all observations per quarter to build quarterly time series as explanatory variables. Hence, we get a quarterly time series with 100 observations from 1993Q1 to 2017Q4. The dependent variable in the basic forecasting regression is the annualized cumulative percentage change in real GDP (inflation: consumer price index) (Estrella and Hardouvelis, 1991; Stock and Watson, 2003):

$$\hat{Y}_{t|t+h} = (400/h)[ln(Y_{t+h}/Y_t)] \tag{10}$$

where Y_t and Y_{t+h} denote the level of real GDP (consumer price index) in period t and $t+h$, $\hat{Y}_{t|t+h}$ is the annualized cumulative percentage change from current quarter t to future quarter $t+h$, and $h = 4$ denotes the forecasting horizon in quarters based on the previous developed quarterly 12-month-ahead fixed horizon sentiment indices. The single forecasting equation is provided by (Ferreira (2018)):

$$\hat{Y}_{t|t+h} = \alpha + \underbrace{\sum_{i=1}^{p} \rho_i \hat{Y}_{t-i}}_{\text{Lag. endog. var.}} + \underbrace{\sum_{k=1}^{n} \sum_{j=0}^{q} \beta_j^k SI(k)_{t-j}}_{\text{Sentiment indices}} + \underbrace{\sum_{m=1}^{3} \sum_{j=0}^{q} \gamma_j^m \text{IN(m)}_{t-j}}_{\text{Control variables}} + \epsilon_{t+h} \tag{11}$$

where $SI(k)$ denotes the respective sentiment index n, and IN(m) represents German leading indicators as control variables. The control variables are also standardized by subtracting the mean from each variable and dividing it by its standard deviation. The forecast horizon h is set to four quarters to capture the 12-month-ahead fixed horizon sentiment indices. To hold the model parsimonious, the lag length p of the endogenous variable is set to one, and q is set equal to 0.

The single forecast regression given in Equation 11 reduces under the simplifying assumption to a simple forecast equation, as suggested by Estrella and Hardouvelis (1991). According to Estrella and Hardouvelis (1991), the overlapping forecasting horizons provoke a moving average error term of order $h-1$, resulting in consistent but inefficient estimates. Therefore, Newey and West (1987)-corrected standard errors are applied with a lag length set equal to three ($h = 4$) in line with Estrella and Hardouvelis (1991).[14]

As control variables for the forecasting regressions, several admitted economic predictors for the German business cycle are introduced:[15]

[14] An automatic selection method for the number of lags is given by Andrews (1991) approximation rule. Another widely used method is to determine the lag length simply to the integer part of $T^{\frac{1}{4}}$, where T is the sample size (Greene, 2012).

[15] For a detailed discussion about German business cycle leading indicators, see Heinisch and Scheufele (2018) and the literature cited therein

- First, the term 'spread' (long-term interest rate minus the short-term interest rate) serves as a monetary control variable. The long-term interest rate serves the yield on debt securities outstanding issued by residents with mean residual maturity of more than nine and up to 10 years (monthly average, source Deutsche Bundesbank (2020)). As the short-term interest rate, the EURIBOR three-month funds money market rate is used (monthly average, source Deutsche Bundesbank (2020)).

- Second, total orders received by the German industry serves as the industry control variable. We take the change over the previous month at constant prices, calendar and seasonally adjusted orders (source: Deutsche Bundesbank (2020))

- Third, the Ifo business climate index as leading business cycle indicator (monthly data, source Ifo institute (2020))

Table 4 presents the in-sample forecasting regression results, including selected business cycle indicators as control variables given by Equation 11. While neither the lagged endogenous variable nor the Ifo business climate index is significantly different from zero, the order inflow and the spread interest rate have a significant impact on the average GDP growth rate. All control variables have the expected sign and a notable magnitude, indicating to a robust specification. Considering the generated sentiment indices, it can be seen that the coefficients are statistically significant only in three out of nine cases. The bag-of-words approach of Bannier1 and both text regression-based sentiments with inflation prediction as response variable (LASSO_INF_P, Ridge_INF_P) are statistically different from zero at conventional significance levels.

Noteworthy is the performance of text regression-based sentiment indices with inflation forecasts as response variables, instead of GDP growth prediction. It seems that this 'wrong' macroeconomic target variable captures the real GDP development as well.[16] This results can be a hint that GDP sub-aggregates, such as investments and consumption, could be promising response variables for text analysis tools to predict GDP growth.

[16]The reason for the correlations are the generated dictionaries. For example, consider the full sample dictionary and weights for LASSO_INF_P in Table A5 again. Words such as 'recovery' ('erholung'), 'stable' ('stabil'), and 'expansive' ('expansiv') have negative weights, whereas words such as 'slow down' ('abkühlung') and 'deficit' ('verlust') have positive weights. All these words are related to GDP growth but have a reversed sign in relation to GDP growth, which explains the correlation and the negative coefficient.

Table 4: Forecasting equations including sentiment indices and control variables for Germany, GDP, 1999Q1 to 2017Q4

	Dependent variable: average growth rate of GDP over the next four quarters									
Lagged endog. var.	0.098	0.092	0.100	0.149	0.113	0.092	0.101	0.120	0.054	0.040
	(0.211)	(0.206)	(0.207)	(0.199)	(0.201)	(0.193)	(0.192)	(0.196)	(0.205)	(0.178)
Order inflow	0.807***	0.706***	0.729***	0.871***	0.828***	0.792***	0.806***	0.718***	0.801***	0.622***
	(0.165)	(0.152)	(0.156)	(0.167)	(0.165)	(0.163)	(0.176)	(0.157)	(0.161)	(0.161)
Interest rate spread	1.191**	1.284**	1.293**	1.131*	1.160*	1.210*	1.192**	0.973*	1.221**	0.780*
	(0.574)	(0.578)	(0.591)	(0.590)	(0.600)	(0.652)	(0.563)	(0.497)	(0.613)	(0.441)
Ifo business climate	0.074	−0.072	−0.067	0.102	0.104	0.065	0.076	0.022	0.042	0.262
	(0.421)	(0.457)	(0.462)	(0.420)	(0.443)	(0.458)	(0.458)	(0.384)	(0.464)	(0.311)
Bannier1		0.628*								
		(0.356)								
Bannier2			0.515							
			(0.342)							
Sharpe1				−0.498						
				(0.363)						
Sharpe2					−0.185					
					(0.303)					
SentiWS						0.127				
						(0.766)				
Lasso_GDP_P							−0.015			
							(0.556)			
Lasso_INF_P								−1.018***		
								(0.275)		
Ridge_GDP_P									0.193	
									(0.577)	
Ridge_INF_P										−1.200***
										(0.287)
Constant	1.509***	1.565***	1.563***	1.422***	1.485***	1.525***	1.504***	1.367***	1.593***	1.409***
	(0.466)	(0.448)	(0.445)	(0.448)	(0.456)	(0.434)	(0.412)	(0.443)	(0.414)	(0.403)
Observations	76	76	76	76	76	76	76	76	76	76
R^2	0.409	0.430	0.424	0.418	0.411	0.410	0.409	0.475	0.411	0.499

Robust (Newey and West, 1987) standard errors in parentheses. Maximum lag length is set to 3 in accordance to Estrella and Hardouvelis (1991). *** p<0.01, ** p<0.05, * p<0.1.

Table 5 presents results regarding inflation in-sample forecasting regressions. Both dictionary-based Bannier sentiment indices have a significant influence on the average growth rate of inflation over the next four quarters. Both sentiment indices are negatively correlated with the target variable.[17] However, most of the generated sentiment indices do not show a significant impact on the average growth rate of inflation over the next four quarters at a conventional significance level.

In brief, changes in the narratives have weak in-sample predictive power on the average growth rate of GDP and inflation over the next four quarters.

4.3.2 Out-of-sample forecasting performance

To evaluate the pseudo out-of-sample predictive power of the narratives, a reduced forecasting model of Equation 11 is used to predict the 12-month-ahead average growth rate of real GDP, namely inflation:

$$\hat{Y}_{t|t+h} = \alpha + \sum_{i=1}^{p} \rho_i \hat{Y}_{t-i} + \sum_{k=1}^{n} \sum_{j=0}^{q} \beta_j^k SI(k)_{t-j} + \epsilon_{t+h} \tag{12}$$

Following Ferreira (2018), we include only the lagged endogenous variable to the forecasting model as an additional regressor. The training sample covers 80 observations for the period from 1993Q1 to 2012Q4. The test sample includes 20 observations for the period from 2013Q1 to 2017Q4, which meets the recommended value of 20 per cent of the full sample (Hyndman and Athanasopoulos, 2018). The model will be re-estimated at each iteration of the pseudo out-of-sample exercise before each one-step-ahead forecast is computed. A simple autoregressive model of order (1) is used as a comparative benchmark model.

In order to evaluate the predictive ability of the narratives, two common forecast evaluation metrics are calculated in a first step. The relative MAE:

$$\text{Relative MAE} = \frac{\frac{1}{T}\sum_{t=1}^{T}\left|e_t^{SI(k)}\right|}{\frac{1}{T}\sum_{t=1}^{T}|e_t^{AR}|} \tag{13}$$

with a linear loss function, and the relative MSE with quadratic loss:

$$\text{Relative MSE} = \frac{\frac{1}{T}\sum_{t=1}^{T}(e_t^{SI(k)})^2}{\frac{1}{T}\sum_{t=1}^{T}(e_t^{AR})^2} \tag{14}$$

[17] The negative polarity of inflation is not surprising, given the finance-specific context of the dictionary. There is no 'right' sign of coefficient; it depends only on the given polarity (or weight).

Table 5: Forecasting equations including sentiment indices and control variables for Germany, Inflation, 1993Q1 to 2017Q4

	Dependent variable: average growth rate of inflation over the next four quarters									
Lagged endog. var.	0.116	0.034	−0.002	0.118	0.136	0.094	0.116	0.240	0.117	0.280
	(0.168)	(0.149)	(0.142)	(0.157)	(0.162)	(0.159)	(0.166)	(0.192)	(0.163)	(0.220)
Order inflow	0.106	0.144**	0.149**	0.075	0.086	0.119	0.104	0.101	0.106	0.092
	(0.069)	(0.073)	(0.070)	(0.069)	(0.068)	(0.074)	(0.075)	(0.066)	(0.069)	(0.068)
Interest rate spread	0.064	−0.007	−0.046	0.118	0.120	0.030	0.063	0.052	0.069	0.036
	(0.168)	(0.165)	(0.159)	(0.158)	(0.160)	(0.184)	(0.169)	(0.168)	(0.187)	(0.161)
Ifo business climate	0.246***	0.331***	0.361***	0.176**	0.174*	0.273***	0.253**	0.231***	0.238**	0.247***
	(0.074)	(0.064)	(0.067)	(0.087)	(0.095)	(0.064)	(0.109)	(0.080)	(0.109)	(0.077)
Bannier1		−0.304*								
		(0.169)								
Bannier2			−0.380**							
			(0.162)							
Sharpe1				0.297						
				(0.189)						
Sharpe2					0.234					
					(0.160)					
SentiWS						−0.155				
						(0.230)				
Lasso_GDP_P							−0.015			
							(0.164)			
Lasso_INF_P								−0.221		
								(0.185)		
Ridge_GDP_P									0.015	
									(0.133)	
Ridge_INF_P										−0.247
										(0.202)
Constant	1.303***	1.390***	1.421***	1.315***	1.284***	1.324***	1.302***	1.111***	1.304***	1.047***
	(0.281)	(0.244)	(0.231)	(0.260)	(0.268)	(0.267)	(0.289)	(0.333)	(0.284)	(0.386)
Observations	76	76	76	76	76	76	76	76	76	76
R^2	0.201	0.252	0.282	0.241	0.235	0.209	0.201	0.224	0.201	0.223

Robust (Newey and West, 1987) standard errors in parentheses. Maximum lag length is set to 3 in accordance to Estrella and Hardouvelis (1991). *** p<0.01, ** p<0.05, * p<0.1.

is calculated by using the respective forecast error e_t of model 12 in relation to the Benchmark AR(1) model. If the value of the relative measure is smaller than 1, the current model outperforms the benchmark model.

In a second step, a Diebold–Mariano test (Diebold and Mariano, 1995; Harvey et al., 1997) is employed to test the out-of-sample forecasting performance. To this end, the null hypothesis of equal predictive accuracy (i.e. equal expected loss) between model and the benchmark model is tested against the one-sided alternative hypothesis that the benchmark model is less accurate:

$$H_0 : L(e_t^{AR}) = L(e_t^{SI(k)}) \text{ versus } H_1 : L(e_t^{AR}) > L(e_t^{SI(k)}) \tag{15}$$

where $L(e_t)$ represents the respective linear loss $L(e_t) = e_t$ or quadratic loss $L(e_t) = e_t^2$. Again, the Newey and West (1987) procedure is applied to correct for autocorrelation and the lag length is set equal to 3 $(h-1)$ following Estrella and Hardouvelis (1991).

Table 6 shows the pseudo out-of-sample forecasting performance results for real GDP growth. The first two columns present the relative forecast performance based on relative MAE and MSE measures. The models including the dictionary-based sentiment indices Bannier1, Bannier2, and SentiWS outperform the Benchmark AR(1) model in both statistical metrics, relative MAE and relative MSE. The forecasting performance of the model with Sharpe1 beats at least the relative MSE. In contrast, forecasting models with regression text-based sentiment indices do not outperform the AR(1) model according to any statistical metric. Statistical tests to check whether the forecasting models including the narratives are more accurate as their autoregressive AR(1) counterparts are given in lines 3 to 6 in Table 6. The Diebold–Mariano tests for linear and quadratic losses do not reject the null hypothesis of equal predictive accuracy for all forecasting models with narratives at conventional significance levels. Thus, the generated sentiment indices do not seem to be a statistically powerful out-of-sample predictor for the average growth rate of GDP over the next four quarters.

Forecasting performance results for inflation are also given in Table 6. On average, the relative forecast performance of the sentiment models are mixed, measured by the relative MAE and MSE. Four model specifications (both Sharpe, Lasso_INF_P, Ridge_INF_P) outperform the benchmark model considering linear loss scenario. Three model specifications (Sharpe1, Lasso_INF_P, Ridge_INF_P) beat the benchmark AR(1) in quadratic loss scenario.

Considering linear Diebold–Mariano tests, the null hypothesis of equal forecast accuracy has to be rejected for two forecasting model specifications,

Table 6: Out of sample forecasting performance - GDP

	Relative MAE	Relative MSE	DM-statistic (linear)	p-value (linear)	DM-statistic (quadratic)	p-value (quadratic)
Dependent Variable: GDP growth						
Bannier1	0.829	0.974	0.870	0.192	0.089	0.465
Bannier2	0.813	0.869	1.111	0.133	0.477	0.317
Sharpe1	1.000	0.995	0.040	0.484	0.387	0.349
Sharpe2	1.002	1.004	-0.860	0.805	-0.990	0.839
SentiWS	0.972	0.966	1.166	0.122	0.880	0.189
Lasso_GDP_P	1.014	1.048	-0.921	0.821	-1.155	0.876
Lasso_INF_P	1.328	1.861	-0.889	0.813	-0.936	0.825
Ridge_GDP_P	1.104	1.191	-2.304	0.989	-2.132	0.984
Ridge_INF_P	1.069	1.215	-0.267	0.605	-0.348	0.636
Dependent Variable: Inflation rate						
Bannier1	1.151	1.344	-1.520	0.936	-1.478	0.930
Bannier2	1.159	1.328	-1.737	0.959	-1.432	0.924
Sharpe1	0.930	0.995	1.947	0.026	0.170	0.433
Sharpe2	0.945	1.010	0.711	0.239	-0.143	0.557
SentiWS	1.122	1.286	-1.345	0.911	-1.426	0.923
Lasso_GDP_P	1.140	1.394	-1.240	0.893	-1.707	0.956
Lasso_INF_P	0.909	0.897	1.307	0.096	0.698	0.242
Ridge_GDP_P	1.165	1.474	-1.344	0.910	-1.770	0.962
Ridge_INF_P	0.949	0.900	1.216	0.112	1.308	0.095

Notes: Dependent variable: average growth rate of GDP over the next four quarters. DM-test statistic and p-values refer to Diebold-Mariano test for predictive accuracy as compared to a simple AR(1) model (Diebold and Mariano, 1995; Harvey et al., 1997). Newey and West (1987)-corrected for autocorrelation ($h = 3$).

at least at a 5 per cent level. Models with Sharpe1 or Lasso_INF_P sentiment indices are significantly more accurate than their Benchmark AR(1) counterpart. Under the assumption of quadratic loss, only the forecast model specification with Ridge_INF_P beat significantly the AR(1) benchmark model.

To summarize, forecasters' narratives have some, at best, predictive ability regarding future inflation in a (pseudo) out-of-sample environment, whereas the predictive power of forecasters' narratives on future GDP growth is at least modest.

5 Discussion and Conclusion

Based on 534 business cycle forecast reports covering 10 German institutions for the period 1993–2017, the paper analysed the information content of German forecasters' narratives for German business cycle forecasts and macroeconomic development. In order to do that, textual analysis is used to convert qualitative text data into quantitative sentiment indices.

In a first step, bag-of-words approaches and text regression methods, and recursive LASSO and ridge estimations are used to transform forecasters' ex-

pectations about the future macroeconomic development into nine sentiment indices.

Second, sentiment analysis shows that the generated sentiment indices vary in their behaviour, pattern, and amplitude. In addition, the sentiment indices differ in their timely relationship to the realized macroeconomic development. Some sentiment indices show nearly a parallel development to the realized value, while other sentiment indices lag behind the real development and a small number of exceptions (partly) lead, compared to the realized value.

Third, sentiment indices are used to test forecast efficiency for GDP growth and inflation forecasts. Using 12-month-ahead fixed horizon forecasts, fixed-effects panel regression results suggest several sentiment indices with informational content for GDP growth and inflation forecasts. German forecasters' narratives can enhance the accuracy of German business cycle forecasts. Overall, the results are in line with the findings of Jones et al. (2020); Sharpe et al. (2020); Clements and Reade (2020). The four-quarter forecast horizon is comparable with the results of Sharpe et al. (2020) for the Fed's Greenbook, whereas findings for the UK show shorter forecast horizons (Jones et al., 2020; Clements and Reade, 2020).

Fourth, a forecasting exercise analysed the predictive power of sentiment indices for realized growth and inflation. This might explain why forecasters' narratives have predictive power for forecast errors. But the forecasting exercise finds weak evidence, at best, for this hypothesis. The results indicate weak in-sample and modest out-of-sample predictive power of the sentiment indices for the future stance of the economy. However, more sophisticated forecasting models, e.g. mixed-data sampling (MIDAS) regression models, could improve the results.

There are several explanatory hypotheses as regards why the narratives contain information that is not exhausted by numerical forecasts. One of these is information rigidity. Based on the hypothesis that forecast revisions have predictive power for forecast errors (Nordhaus, 1987), Coibion and Gorodnichenko (2015) and Dovern et al. (2015) find some hints supporting this hypothesis using tests for numerical forecasts in an international setting. Kirchgässner and Müller (2006) also find some evidence that German forecasters are reluctant to revise numerical forecasts. In a similar vein, forecasters' narratives could be faster adjusted than their numerical counterparts. Sharpe et al. (2020) analysis for sticky point forecasts could only find weak evidence, at best, for this hypothesis. Another explanatory approach for the predictive power of forecasters' narratives is the 'modal-forecast explanation' (Sharpe et al., 2020, p. 5). This hypothesis is based on the concept that the sentiment indices are particularly informative about tail risks, whereas

numerical forecasts unbalance the risks because they are modal rather than mean forecasts. Sharpe et al. (2020) findings suggest such an interpretation. An additional explanation could be that the forecast narrative offers a wider scope for individuality than the quantitative forecast. The numerical forecast is limited to a number. And the production of the forecasts also depends on the institutes' hierarchy and other influencing factors (see e.g. Fritsche and Heilemann, 2010, for the Joint Diagnosis). Thus, the forecast report may allow the forecaster a higher degree of freedom. An study of the general issue—why forecasters' narratives have predictive power for forecast errors—could form part of further research.

Last but not least, there is not a single sentiment index or sentiment analysis approach which is generally superior to other methods. The forecast-specific dictionary (Sharpe et al., 2020) and text regression methods perform well in tests for forecast efficiency. Considering the predictive power for GDP growth and inflation, dictionary-based approaches and text regression methods perform relatively poorly. However, the sentiment analysis could be improved in further research using more sophisticated text analysis and machine learning tools.

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Appendix

Appendix: Tables and Figures

Table A1: List of included institutions and publications

Institution	Dates	Publication schedule	Source
German central bank (Deutsche Bundesbank)	2007 - 2017	bi-annually	Monatsberichte der Deutschen Bundesbank
German Institute of Economic Research (DIW Berlin)	1993 - 2017	bi-annually (1993-2004), quarterly (2005-2017)	Wochenbericht des DIW
Joint forecast of the German economic research institutes (Gemeinschaftsdiagnose)	1993 - 2017	bi-annually	various publications
Hamburg Institute of International Economics (HWWI) (HWWA until 2006)	1993 - 2017	bi-annually (1993-2006), quarterly (2005-2017)	Konjunktur von morgen (1990-1996), Wirtschaftsdienst (1997-2017), occasionally press releases from 2015
Ifo Institute Munich	1993 - 2017	bi-annually	Monatsberichte des ifo Instituts für Wirtschaftsforschung (1993-2000), ifo Schnelldienst (2001-2017)
Kiel Institute for World Economics (IfW)	1993 - 2017	quarterly	Die Weltwirtschaft (1993-2005), Kieler Diskussionsbeiträge (2006-2014), Kieler Konjunkturberichte (2015-2017)
Macroeconomic Policy Institute (IMK)	2005 - 2017	quarterly	IMK Report
German Economic Institute (IW Köln)	1995 - 2017	annually (1995-2006), bi-annually (2007-2016)	IW Trends
Institute for Economic Research Halle (IWH)	1997 - 2017	bi-annually (1997-2000), quarterly (2001-2017)	Wirtschaft im Wandel (1997-2012), Konjunktur aktuell (2013-2017), occasionally press releases
Rhine-Westphalia Institute for Economic Research (RWI)	2006 - 2017	bi-annually (2006-2012), quarterly (2013-2017)	RWI-Konjunkturberichte

Table A2: Forecasting specific word list: positive words (205 words)

English	German	English	German
assurance	Zusicherung	endorse	billigen
assure	versichern	energetic	energetisch
attain	erreichen	engage	engagieren
attractive	attraktiv	enhance	verbessern
auspicious	vielversprechend	enhancement	Verbesserung
backing	Unterstützung	enjoy	genießen
befitting	angemessen	enrichment	Anreicherung
beneficial	vorteilhaft	enthusiasm	Begeisterung
beneficiary	Begünstigter	enthusiastic	enthusiastisch
benefit	Vorteil	envision	vorstellen
benign	gutartig	excellent	exzellent
better	besser	exuberance	Überschwang
bloom	Blütezeit	exuberant	überschwänglich
bolster	Nackenrolle	facilitate	erleichtern
boom	Boom	faith	Glaube
boost	Verstärkung	favor	Gefälligkeit
bountiful	freigiebig	favorable	günstig
bright	hell	feasible	durchführbar
buoyant	schwungvoll	fervor	Inbrunst
calm	ruhig	filial	kindlich
celebrate	feiern	flatter	flacher
coherent	kohärent	flourish	blühen
comeback	wiederbelebung	fond	zärtlich
comfort	Komfort	foster	fördern
comfortable	komfortabel	friendly	freundlich
commend	empfehlen	gain	Gewinn
compensate	kompensieren	generous	großzügig
composure	Gelassenheit	genuine	echt
concession	Konzession	good	gut
concur	übereinstimmen	happy	glücklich
conducive	förderlich	heal	heilen
confide	anvertrauen	healthy	gesund
confident	selbstbewusst	helpful	hilfreich
constancy	Beständigkeit	hope	Hoffnung
constructive	konstruktiv	hopeful	hoffnungsvoll
cooperate	kooperieren	hospitable	gastfreundlich
coordinate	Koordinate	imperative	unerlässlich
credible	glaubwürdig	impetus	Impulsgeber
decent	anständig	impress	beeindrucken
definitive	definitiv	impressive	beeindruckend
deserve	verdienen	improve	verbessern
desirable	wünschenswert	improvement	Verbesserung
discern	erkennen	inspire	inspirieren
distinction	Unterscheidung	irresistible	unwiderstehlich
distinguish	unterscheiden	joy	Freude
durability	Haltbarkeit	liberal	liberal
eager	begierig	lucrative	lukrativ
earnest	ernst	manageable	überschaubar
ease	Leichtigkeit	mediate	vermitteln
easy	einfach	mend	ausbessern
encourage	ermutigen	mindful	achtsam
encouragement	Ermutigung		

Table A2 cont., Forecasting specific word list: positive words (205 words)

English	German	English	German
moderation	Moderation	revival	Aufschwung
onward	vorwärts	revive	wieder aufleben
opportunity	Gelegenheit	ripe	reif
optimism	Optimismus	rosy	rosig
optimistic	optimistisch	salutary	heilkräftig
outrun	überschreiten	sanguine	blutrot
outstanding	ausstehend	Satisfactory	Zufriedenstellend
overcome	überwinden	Satisfy	Befriedigen
paramount	hervorragend	Sound	Sound
particular	speziell	Soundness	Solidität
patience	Geduld	Spectacular	Spektakulär
patient	Patient	Stabilize	Stabilisieren
peaceful	friedlich	Stable	Stabil
persuasive	überzeugend	Stable	Stabil
pleasant	angenehm	Steadiness	Stetigkeit
please	bitte	Steady	Langsam
pleased	zufrieden	Stimulate	Stimulieren
plentiful	reichlich	Stimulation	Stimulation
plenty	Fülle	Subscribe	Abonnieren
positive	positiv	Succeed	Erfolgreich
potent	stark	Success	Erfolg
precious	kostbar	Successful	Erfolgreich
pretty	hübsch	Suffice	Es genügt
progress	Fortschritt	Suit	Anzug
progressive	progressiv	Support	Unterstützung
prominent	bekannt	Supportive	Unterstützende
promise	Versprechen	Surge	Surge
prompt	Eingabeaufforderung	Surpass	Übertrifft
proper	ordentlich	Sweeten	Süßstoff
prosperity	Wohlstand	Sympathetic	Sympathisch
rally	Kundgebung	Sympathy	Mitgefühl
readily	bereit	Synthesis	Synthese
reassure	beruhigen	Temperate	Gemäßigt
receptive	empfänglich	Thorough	Gründlich
reconcile	versöhnen	Tolerant	Tolerant
refine	verfeinern	tranquil	ruhig
reinstate	wiederherstellen	tremendous	riesig
relaxation	Entspannung	undoubtedly	zweifellos
reliable	zuverlässig	unlimited	unbegrenzt
relief	Erleichterung	upbeat	optimistisch
relieve	entlasten	upgrade	Upgrade
remarkable	bemerkenswert	uplift	Auftrieb
remarkably	bemerkenswert	upside	aufwärts
repair	Reparatur	upward	nach oben
rescue	Rettung	valid	gültig
resolve	auflösen	viable	tragfähig
resolved	gelöst	victorious	siegreich
respectable	respektabel	virtuous	tugendhaft
respite	Aufschub	vitality	Vitalität
restoration	Wiederherstellung	warm	warm
restore	wiederherstellen	welcome	willkommen

Notes: Own translation based on DeepL Pro. Based on the English version (Sharpe et al., 2020).

Table A3: Forecasting specific word list: negative words (103 words)

English	German	English	German
adverse	nachteilig	hurt	verletzt
afflict	belasten	illegal	illegal
alarming	beunruhigend	insecurity	Unsicherheit
apprehension	Besorgnis	insidious	heimtückisch
apprehensive	ängstlich	instability	Instabilität
awkward	unangenehm	interfere	eingreifen
bad	schlecht	jeopardize	gefährden
badly	schlecht	jeopardy	Gefahr
bitter	bitter	lack	Mangel
bleak	trostlos	languish	schmachten
bug	Fehler	loss	Verlust
burdensome	beschwerlich	mishap	Missgeschick
corrosive	korrosiv	negative	negativ
danger	Gefahr	nervousness	Nervosität
daunting	beängstigend	offensive	beleidigend
deadlock	Sackgasse	painful	schmerzhaft
deficient	unzulänglich	paltry	armselig
depress	niederdrücken	pessimistic	pessimistisch
depression	Krise	plague	Plage
destruction	Vernichtung	plight	Notlage
devastation	Abbau	poor	schlecht
dim	schwach	recession	Rezession
disappoint	enttäuschen	sank	gesunken
disappointment	Enttäuschung	scandal	Skandal
disaster	Katastrophe	scare	schreck
discomfort	Unbehagen	sequester	absondern
discouragement	Entmutigung	sluggish	träge
dismal	trostlos	slump	Einbruch
disrupt	unterbrechen	sour	sauer
disruption	Störung	sputter	spritzen
dissatisfied	unzufrieden	stagnant	stagnierend
distort	verzerren	standstill	Stillstand
distortion	Verzerrung	struggle	kämpfen
distress	Notlage	suffer	ertragen
doldrums	Flaute	terrorism	Terrorismus
downbeat	deprimierend	threat	Bedrohung
emergency	Notfall	tragedy	Tragödie
erode	erodieren	tragic	tragisch
fail	scheitern	trouble	Ärger
failure	Versagen	turmoil	Aufruhr
fake	Fälschung	unattractive	unattraktiv
falter	zögern	undermine	untergraben
feeble	schwach	undesirable	unerwünscht
feverish	fieberhaft	uneasiness	Unbehagen
fragile	zerbrechlich	uneasy	unbehaglich
gloom	Tristesse	unfavorable	ungünstig
gloomy	düster	unforeseen	unvorhergesehen
grim	grimmig	unprofitable	unrentabel
harsh	rau	unrest	Unruhe
havoc	Verwüstung	violent	gewalttätig
hit	treffen	war	Krieg
horrible	schrecklich		

Notes: Own translation based on DeepL Pro. Based on the English version (Sharpe et al., 2020).

Table A4: Dictionary and weights - Lasso GDP (71 words)

Words	Weight	Words	Weight
aufschwung	0.0939	steuersenkungen	0.0000
fortsetzung	0.0458	schwellenländ	0.0000
fortgesetzt	0.0358	fiskalischen	0.0000
erreicht	0.0294	inlandsnachfrag	0.0000
bewirkt	0.0272	beachten	0.0000
schwungvol	0.0260	fort	0.0000
erweiterungsinvestitionen	0.0246	einstellen	0.0000
steigend	0.0217	historisch	0.0000
dynamik	0.0207	absatzperspektiven	-0.0009
verbrauchskonjunktur	0.0192	abschwung	-0.0015
einsparmaßnahmen	0.0188	erholen	-0.0017
exportdynamik	0.0180	geld	-0.0026
japan	0.0159	konjunkturschwäch	-0.0030
schwellenländern	0.0134	bezugsdau	-0.0047
guten	0.0100	historischen	-0.0050
südostasien	0.0094	minus	-0.0053
westdeutschland	0.0092	anpassungen	-0.0061
belaufen	0.0087	extrem	-0.0065
abflachen	0.0081	massiv	-0.0083
ostdeutschland	0.0080	konjunkturpaket	-0.0118
hohen	0.0059	getroffen	-0.0174
lohnabschlüss	0.0052	talfahrt	-0.0187
betragen	0.0048	verschlechterten	-0.0220
drittel	0.0047	schwachen	-0.0247
industrieländern	0.0039	verschlechtert	-0.0253
turbulenzen	0.0038	schlechten	-0.0332
vorkrisenniveau	0.0018	schrumpfen	-0.0337
erreichten	0.0014	unterauslastung	-0.0342
läßt	0.0011	einbruch	-0.0342
außenwert	0.0008	unterhang	-0.0389
reichlich	0.0006	entlassungen	-0.0392
unterschied	0.0003	tief	-0.0479
wachstum	0.0002	reduzieren	-0.0480
längerfristigen	0.0001	stabilisierung	-0.1052
arbeitslosenversicherung	0.0000	drastisch	-0.1427
wachstumspakt	0.0000		

Notes: Full sample example. The table presents the LASSO text regression-based dictionary with weights over the full corpus from 1993-2017. The weights are rounded to the 4th decimal. Response variable: GDP forecast (12-month-ahead fixed horizon forecast).

Table A5: Dictionary and weights - Lasso inflation (69 words)

Words	Weight	Words	Weight
investoren	0.0369	ältere	0.0005
lockerung	0.0232	mehrwertsteu	0.0001
tarifabschlüss	0.0229	mehrwertsteuererhöhung	0.0000
nachlassenden	0.0201	stützt	0.0000
abkühlung	0.0200	flüchtling	-0.0005
nahrungsmittelpreis	0.0198	jahresverlaufsr	-0.0006
arbeitslosenversicherung	0.0181	unsich	-0.0009
halb	0.0171	abwertung	-0.0010
durchsetzen	0.0168	esvg	-0.0012
treuhandanstalt	0.0161	leistungsausweitungen	-0.0013
zurückbilden	0.0127	abnehmenden	-0.0019
westeuropa	0.0125	stufe	-0.0034
westdeutsch	0.0119	einbruch	-0.0035
kurzfristigen	0.0117	investitionsausgaben	-0.0035
westdeutschen	0.0112	gang	-0.0038
eingestellt	0.0109	stützen	-0.0039
lohnabschlüss	0.0098	gesamt	-0.0039
verlust	0.0096	drastisch	-0.0052
gute	0.0084	land	-0.0055
bundesrepublik	0.0079	kranken	-0.0055
steuererhöhungen	0.0079	entscheidungen	-0.0079
zahlungen	0.0079	zugang	-0.0083
insolvenzgeldumlag	0.0075	krankenkassen	-0.0096
preisauftrieb	0.0072	festigung	-0.0108
staatsausgaben	0.0066	kindergeld	-0.0142
lohnpolitik	0.0052	bundesverfassungsgericht	-0.0149
sparneigung	0.0049	niedrigen	-0.0155
tätigen	0.0039	wirkung	-0.0175
konjunkturindikatoren	0.0026	expansiv	-0.0204
abschreibungsbedingungen	0.0025	stabil	-0.0255
inlandskonzept	0.0019	erholung	-0.0296
gelegen	0.0019	unterauslastung	-0.0335
beitragssatz	0.0018	arbeitslosigkeit	-0.0547
schwächeren	0.0015	gesunkenen	-0.0582
mäßig	0.0013		

Notes: Full sample example. The table presents the LASSO text regression-based dictionary with weights over the full corpus from 1993-2017. The weights are rounded to the 4th decimal. Response variable: inflation forecast (12-month-ahead fixed horizon forecast).

Table A6: Dictionary and weights - Ridge GDP - Top 30 positive and negative Words

Positive words	Weight	Negative words	Weight
fortsetzung	0.0095	wirken	-0.0061
fortsetzen	0.0081	geld	-0.0062
zunehmen	0.0081	verhindert	-0.0063
aufschwung	0.0079	druck	-0.0063
dynamik	0.0075	einbruch	-0.0064
schwungvol	0.0074	instrument	-0.0066
steigend	0.0071	massiv	-0.0067
bleiben	0.0071	zurückgehen	-0.0069
privaten	0.0067	einmalig	-0.0070
steigenden	0.0066	rückgang	-0.0071
erweiterungsinvestitionen	0.0065	talfahrt	-0.0074
bleibt	0.0063	einstellen	-0.0075
verbessert	0.0063	schlechten	-0.0077
günstig	0.0060	reduzieren	-0.0078
fortgesetzt	0.0059	unterauslastung	-0.0079
hohen	0.0058	rückläufigen	-0.0079
bewirkt	0.0057	schwachen	-0.0080
verbrauchskonjunktur	0.0056	schrumpfen	-0.0085
investitionsdynamik	0.0056	verschlechtert	-0.0085
betragen	0.0055	unterhang	-0.0087
erreicht	0.0055	erholen	-0.0087
höheren	0.0053	tief	-0.0087
erstmal	0.0051	unternehmen	-0.0088
lohnabschlüss	0.0050	stabilisieren	-0.0088
kräftige	0.0050	entwicklung	-0.0088
investitionsklima	0.0050	sinken	-0.0094
kräftigen	0.0049	verschlechterten	-0.0096
konjunkturaufschwung	0.0049	entlassungen	-0.0107
stütze	0.0049	stabilisierung	-0.0117
guten	0.0048	drastisch	-0.0118

Notes: The table presents the Ridge text regression-based dictionary with weights over the full corpus from 1993-2017. The weights are rounded to the 4th decimal. Response variable: GDP forecast (12-month ahead fixed horizon forecast).

Table A7: Dictionary and weights - Ridge inflation - Top 30 positive and negative Words

Positive words	Weight	Negative words	Weight
unternehmen	0.0085	ursächlich	-0.0037
tarifabschlüss	0.0073	preiserhöhungsspielräum	-0.0038
durchsetzen	0.0072	zehnjährig	-0.0038
real	0.0071	durchgeführt	-0.0038
investoren	0.0067	wirken	-0.0039
trotz	0.0062	eingeschränkt	-0.0039
lohnabschlüss	0.0061	zentralbank	-0.0039
konjunkturindikatoren	0.0060	krankenkassen	-0.0040
nachlassenden	0.0059	festigung	-0.0040
nahrungsmittelpreis	0.0059	gang	-0.0040
mäßig	0.0052	kranken	-0.0041
abkühlung	0.0052	drastisch	-0.0042
lockerung	0.0051	quartalsdurchschnitt	-0.0043
halb	0.0050	jahresveränderungsr	-0.0045
aufwärtsentwicklung	0.0049	druck	-0.0045
marktanteil	0.0049	früherer	-0.0046
transferzahlungen	0.0048	profitieren	-0.0046
eckdaten	0.0047	bundesverfassungsgericht	-0.0051
gesamtwirtschaftlich	0.0047	erholung	-0.0051
schwächeren	0.0045	abnehmenden	-0.0051
tendenziel	0.0045	stabil	-0.0054
steuererhöhungen	0.0045	erwerbspersonen	-0.0054
beleben	0.0044	stützen	-0.0056
bestimmt	0.0044	unterauslastung	-0.0058
hohen	0.0043	niedrigen	-0.0059
sparneigung	0.0043	bleibt	-0.0061
vordergrund	0.0041	gesunkenen	-0.0068
inlandskonzept	0.0041	arbeitsmarkt	-0.0084
verbesserung	0.0040	bleiben	-0.0095
lohnpolitik	0.0040	arbeitslosigkeit	-0.0113

Notes: The table presents the Ridge text regression-based dictionary with weights over the full corpus from 1993-2017. The weights are rounded to the 4th decimal. Response variable: inflation forecast (12-month ahead fixed horizon forecast).